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Broadband Infrastructure Construction and Consumption Inequality

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Abstract

This study examined the impact of broadband infrastructure on household consumption inequality in China. Using panel data from 2012 to 2018 and employing a staggered difference-in-differences design, it found that the Broadband China program reduced relative consumption deprivation. The effect was driven primarily by increases in household income and social connections. Reductions in inequality were more pronounced in rural and inland areas, among younger households, and in regions with higher market segmentation. By contrast, an earlier policy that improved Internet speed without expanding access was associated with increased inequality. The findings suggest that digital infrastructure can shape the distributional effects of growth by improving access for disadvantaged groups.

Keywords: Broadband China program, consumption inequality, pilot city establishment, relative deprivation

JEL codes: D12, O33

I. Introduction

Household consumption inequality has become an important measure of economic well-being, especially in contexts where income is volatile or fails to fully capture access to goods and services. In comparison with income or wealth, consumption reflects actual living standards and is more stable over time (Meyer and Sullivan, 2011). In China, the rapid growth over recent decades has improved average welfare but has also been accompanied by rising disparities in household consumption (Yao and Zang, 2022). These disparities reflect not only differences in income but also unequal access to infrastructure, markets, and networks. Understanding the sources of these gaps is important for evaluating the distributional consequences of structural change.

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Recent research has highlighted the potential of digital technologies to narrow such gaps. Studies show that tools like e-commerce, mobile payments, and digital financial services can help marginalized households access goods and markets, reducing consumption inequality and improving workers' job quality (Luo and Li, 2022; Yang and Zhang, 2022; Jiang et al., 2023; Wang et al., 2024). These technologies, however, depend critically on the availability of broadband infrastructure. Internet access has expanded rapidly in China but significant spatial disparities remain (Liu and Wang, 2019). Earlier studies have often focused on adoption or usage outcomes rather than the underlying infrastructure that enables such outcomes. As a result, little is known about whether improving digital infrastructure, rather than digital services per se, can reduce household-level consumption inequality.

This study examined the effects of broadband infrastructure on household consumption inequality in China, addressing a gap in the literature. The analysis focused on the Broadband China program, a nationwide program launched in 2013 to expand Internet coverage, particularly in underserved regions. Four waves of panel data from the China Labor Dynamics Survey (CLDS) were combined with a staggered difference-in-differences (DID) design to estimate the causal impact of broadband rollout on relative consumption deprivation. The results indicated that the program reduced household-level consumption inequality significantly, primarily through increases in income and social capital. The effects were more pronounced in rural and inland regions, among younger households, and in areas with higher market segmentation. By contrast, an earlier policy that increased Internet speed without expanding access was associated with greater inequality. These findings suggest that differences in infrastructure rollout can lead to substantial variation in household consumption outcomes and that digital expansion can influence inequality depending on the nature of access.

This study contributes to the literature on digital infrastructure and inequality in three ways. First, it provides causal evidence on how broadband expansion can affect household consumption inequality. Earlier work focused on digital services like e-commerce and finance but the role of basic Internet infrastructure received less attention (Luo and Li, 2022; Yang and Zhang, 2022). This study examined the Broadband China program using a staggered DID design and panel data to estimate its impact on relative consumption deprivation. Second, it measured inequality at the household level using a deprivation index based on local reference groups. Most existing studies rely on regional indices such as the Gini coefficient (Zhang et al., 2020), which may miss differences within communities. The approach taken in the current study allows for a more detailed view of how inequality can change across different households (Liao, 2022). Third, this study compared two major Internet policies in China – one focused on expanding access and the other focused on improving speed. This comparison shows that improving access had a stronger link to the reduction in inequality, especially in rural and segmented markets (van Deursen and van Dijk, 2019; Liu and Wang, 2021).

The remainder of the paper is structured as follows. Section II outlines the policy background, reviews the relevant literature, and develops the research hypotheses. Section III details the research design and describes the data. Section IV presents the empirical results and robustness checks. Section V investigates the underlying mechanisms. Section VI offers further analysis, and Section VII concludes with key findings and policy implications.

II. Policy background and research hypotheses

1. Policy background

Broadband networks, as a critical component of strategic public infrastructure, play a pivotal role in catalyzing investment and facilitating information-driven consumption. Similar network infrastructure initiatives have been implemented in various countries. For example, in the early 2000s, the Norwegian government launched a nationwide initiative to expand affordable broadband access across the country (Hvide et al., 2024). In China, Internet access began in 1994, when the Institute of High Energy Physics established the nation's first Transmission Control Protocol/Internet Protocol connection with the Stanford Linear Accelerator Center. However, prior to the rollout of broadband Internet in 2000, the widespread adoption of Internet services was significantly constrained by slow connection speeds and high access costs. These limitations were alleviated gradually through a series of network acceleration initiatives and the deployment of asymmetric digital subscriber line technology, which collectively paved the way for the rapid expansion of Internet access across the country.

To accelerate the development of broadband infrastructure, the State Council introduced the "Broadband China program and its Implementation Plan" in 2013 (referred to here as Broadband China). This initiative sought to tackle key obstacles to broadband network development, including insufficient signal coverage in public spaces, pronounced regional and urban–rural disparities, and a deficiency in technological innovation. Its primary objective was to achieve both extensive coverage and high performance in broadband expansion. To fulfill the objective of "broad coverage," the strategy prioritized comprehensive broadband access in both urban and rural areas, setting a specific target to connect over 98 percent of administrative villages. To reflect the goal of "high quality," the policy also introduced clear performance benchmarks: 50 Mbps for urban households, 12 Mbps for rural households, and 100 Mbps access for at least 50 percent of urban households.

To support the rollout of the Broadband China program, the Ministry of Industry and Information Technology and the National Development and Reform Commission identified 120 cities or city clusters as pilot areas, initiating the program in successive waves during 2014, 2015, and 2016. After 3 years of development, these pilot regions set benchmarks for broadband infrastructure and applications, providing demonstrative models for other regions across the country. Since the launch of the strategy, China's broadband infrastructure has seen remarkable improvement. Network coverage has expanded significantly, transmission and access capabilities have been enhanced, and broadband technology has advanced substantially. As a result, an integrated industrial ecosystem has emerged, accompanied by steady progress in application services. Concurrently, digital sectors such as e-commerce, software outsourcing, cloud computing, and the Internet of Things have experienced rapid growth. According to the 49th Statistical Report on China's Internet Development, China's Internet user base reached 1 billion by December 2021, representing a penetration rate of 73 percent. As of the same reporting period, there were 35.93 million registered domain names and 63,052 allocated Internet Protocol Version 6 addresses. The cumulative number of operational 5G base stations reached 1.425 million, highlighting the rapid expansion and deepening integration of digital infrastructure nationwide.

2. Research hypotheses

The Organisation for Economic Co-operation and Development defined the digital divide as the gap among individuals, households, businesses, and regions of varying socioeconomic status in both access to information and communication technologies (ICTs) (the access divide) and the ability to use them effectively (the use divide) (OECD, 2001). This persistent divide could amplify the "Matthew effect," whereby those with greater access to ICTs continue to accumulate advantages whereas those without such access fall further behind, thus widening consumption disparities across social groups (Wang et al., 2023). In this context, network infrastructure, as a form of public good, enhances Internet accessibility directly and plays a critical role in narrowing the access divide. Empirical evidence from both international and domestic studies has demonstrated that investments in network infrastructure can contribute to mitigating both the access and use divides, fostering broader digital inclusion, and reducing disparities in ICT adoption (Chinn and Fairlie, 2007; Meng et al., 2023).

In contrast to traditional forms of infrastructure, digital infrastructure facilitates rapid and expansive dissemination of information over time and space, and exhibits distinctive features such as network externalities and spillover effects (Röller and Waverman, 2001). It is instrumental in reducing transaction costs, expanding the range of consumer choices, and improving overall consumer welfare. Network infrastructure also facilitates the adoption of emerging technologies, such as information access, e-commerce, and online payments, helping overcome geographical barriers that have historically constrained consumption (Niu et al., 2022). By enabling these tools, it transforms consumption patterns among populations traditionally marginalized by limited information access. Empirical studies have substantiated these mechanisms. Using a differentiated product demand model, Duch-Brown et al. (2017) demonstrated that cyberinfrastructure enhanced consumer access to a broader array of goods while reducing prices and search costs. Similarly, Fan et al. (2018) highlighted that online transactions bypassed spatial and temporal limitations, allowing residents in smaller or more remote cities to obtain a wider variety of goods and services at reduced costs. Collectively, these findings highlight the importance of network infrastructure in bridging the digital divide, ensuring more equitable access to the digital dividend, and narrowing intra-regional consumption disparities.

Hypothesis 1: Improved broadband infrastructure can significantly reduce regional consumption disparities by enhancing access to digital markets.

Consumption deprivation varies at the individual level. Viewed through the lens of the “first-tier” digital divide, those in historically underserved regions are more likely to realize substantial benefits. Unlike traditional infrastructure, which provides direct and immediate utility, Internet access requires upfront investment, including the cost of ICT devices and the effort involved in acquiring relevant information, making it less accessible to certain segments of the population. By expanding broadband coverage to underdeveloped areas, including rural regions and cities in central and western China, the Broadband China program has the potential to reduce consumption deprivation among disadvantaged groups. However, although the access gap has narrowed over time, a higher order digital divide remains. Adoption and effective utilization of digital technologies continue to be shaped by demographic factors (Liu and Wang, 2021). The technology acceptance model posits that technology adoption is influenced by users’ perceived usefulness and perceived ease of use. Variations in these perceptions across demographic groups result in heterogeneous responses to broadband infrastructure (Zhang et al., 2020; Wang et al., 2023). As van Deursen and van Dijk (2019) pointed out, even in areas where Internet access is widespread, disparities in digital skills persist and continue to reinforce the digital divide. The following hypothesis is based on these insights.

Hypothesis 2: Network infrastructure can have a greater impact on reducing consumption deprivation among households in previously underserved regions and among individuals with higher levels of digital literacy.

III. Research design and data description

1. Research design

This analysis treated the Broadband China pilot program as an exogenous shock and employed a staggered DID model to estimate its impact on household consumption inequality. It also addressed potential endogeneity issues observed commonly in prior research, particularly those arising from measurement errors in Internet user base size or composite Internet indicators (Zhang et al., 2020; Qiu et al., 2021).

Following the framework proposed by Leng (2022), the model was specified as follows:

$$RCD_{ijt} = \beta_0 + \beta_1 Broadband_{jt} + \gamma \boldsymbol{Control}_{ijt} + \tau_i + \nu_t + \varepsilon_{ijt}. \tag{1}$$

The dependent variable, RCD_{ijt}, captures the relative consumption deprivation of household i in city j at year t. The core explanatory variable, *Broadband*, is measured as the interaction of a year dummy variable and a group dummy variable. Specifically, *Broadband* equals 1 if city j is designated as a Broadband China pilot city in year t, and 0 otherwise. The coefficient of the interaction term β_1 reflects the impact of pilot city designation on relative household consumption deprivation and is hypothesized to be negative. ***Control*** denotes a set of household-level control variables, including the *hukou* of the household head, average educational attainment, the ratio of unhealthy family members, the child dependency ratio, family indebtedness, house ownership, financial market participation, and community type. τ represents the household fixed effects, ν captures the year fixed effects, and ε is the error term. This specification effectively controls time-invariant differences between the treatment and control groups and also group-specific time trends.

2. Data description

This study drew on data from the CLDS, including the 2012 baseline survey and the follow-up waves conducted in 2014, 2016, and 2018.[1] Initiated by the Social Science Survey Center at Sun Yat-sen University, the CLDS provides nationally representative data on China's working-age population (aged 15–64). The dataset covers 160 cities and tracks over 20,000 individuals from approximately 14,000 households. It provides detailed information on demographic characteristics, socioeconomic status, and household conditions, offering high-quality data for analyzing household consumption inequality. Notably, the survey records household consumption for the previous year rather than the survey year. To ensure temporal consistency with the timing of pilot city implementation, survey years were adjusted forward by 1 year. To reduce

[1]This study focused on the 2014−2016 period, which corresponds to the launch year of the Broadband China program.

outlier samples, the data were also winsorized at the 1st and 99th percentiles. For other variables, observations with missing values, including "don't know" and refusal responses, were excluded, yielding a final sample of 40,280 observations. City-level variables were sourced from the *China Urban Statistical Yearbook.*

3. Description of variables

The dependent variable was relative consumption deprivation. Earlier studies typically measured consumption inequality using the Gini coefficient or the Theil index. These indices captured aggregate inequality within a group or region but they failed to reflect the heterogeneous impact of network infrastructure on intra-regional household deprivation. Regions with similar Gini coefficients, for example, could differ significantly in the depth and distribution of acute household-level deprivation. As a result, aggregate indices provided limited insight into the welfare implications for individuals. According to the theory of relative deprivation (Runciman, 1966), relative consumption deprivation measures the extent to which a household's consumption level falls short compared to that of more advantaged members within its reference group. Unlike conventional measures focusing on overall dispersion, this approach identifies the specific shortfall experienced by each household within its local context.

Building on Kakwani (1984), the current study constructed a relative deprivation index by aggregating the consumption shortfalls between each household and all higher-consuming households within its reference group, yielding the Kakwani index. Specifically, let n denote the number of households in the reference group. Per capita consumption expenditures were ranked in ascending order, yielding the distribution $X = (x_1, x_2, ..., x_n)$, such that $x_1 \leqslant x_2 \leqslant ... \leqslant x_n$. Thus, the relative deprivation experienced by household i, whose expenditure is x_i, was calculated using the following expression:

$$RCD_i = \frac{1}{n\mu_X} \sum\nolimits_{j=i+1}^{n} \left(x_j - x_i \right) = \gamma_{x_i}^{+} \left[\left(\mu_{x_i}^{+} - x_i \right) / \mu_X \right], \tag{2}$$

where $\mu_{x_i}^{+}$ denotes the average consumption of households in group X whose expenditures exceed x_i, and $\gamma_{x_i}^{+}$ represents the proportion of households in group X with higher consumption than x_i. To calculate the Kakwani deprivation index, the individual's village or community was designated as the reference group, reflecting local price variations and the geographic scope of individual activity.[2]

[2]Theoretical literature on inequality measurement often emphasizes that aggregate inequality indices are constructed by aggregating individual-level measures (Liao, 2022). Kakwani (1984) introduced a relative deprivation curve analogous to the Lorenz curve, formalized its properties, and demonstrated its use in deriving the Gini coefficient. Accordingly, the weighted average of the individual-level Kakwani indices used in this study corresponded to the overall Gini coefficient (Yitzhaki, 1979).

The core explanatory variable, Broadband China pilot city establishment (*Broadband*), captured the effect of the Broadband China pilot city designation and was constructed as the interaction between a year dummy variable (*Year*) and a group dummy variable (*Treated*). The time dummy took a value of 1 for observations in years after the pilot city designation and 0 otherwise. The group dummy was set at 1 for cities designated as pilot cities, including those in the Chang−Zhu−Tan city cluster, and 0 for all other cities. Information on pilot city designations was obtained from official records released by China's Ministry of Industry and Information Technology. To identify the treatment group, pilot cities were matched with respondents' prefecture-level city identifiers as recorded in the CLDS database.

Drawing on Luo and Li (2022), the model included a set of control variables to account for factors that may affect relative household consumption deprivation. Specifically, the control variables included the *hukou* status of the household head, average household age, average educational attainment of adults,[3] the proportion of unhealthy members,[4] the child dependency ratio (defined as the share of household members under age 16), household indebtedness, type of homeownership, participation in financial markets (e.g., holdings of stocks, funds, or bonds), and the type of community in which the household resides. The household-level data are drawn from the CLDS survey database, and descriptive statistics for each variable are presented in Table 1.

Table 1. Descriptive statistics

Variable	Control group (*Treated* = 0)				Experimental group (*Treated* = 1)			
	Mean	Standard deviation	Min.	Max.	Mean	Standard deviation	Min.	Max.
Relative deprivation in consumption (Community/village)	0.468	0.257	0	1	0.448	0.253	0	1
Hukou of the household head (nonagricultural = 1)	0.304	0.460	0	1	0.435	0.496	0	1
Average age	41.765	13.767	10	97	42.454	13.278	13	97

(Continued on the next page)

[3]According to the original questionnaire, no schooling = 1; primary school = 2; junior high school = 3; senior high school = 4; vocational high school = 5; technical school = 6; secondary school = 7; tertiary school = 8; bachelor's degree = 9; master's degree = 10; and doctorate = 11.

[4]The health status of household members was characterized by self-assessed health, with individuals who reported that they were "healthy" or "very healthy" coded as 0 and all others coded as 1, indicating "unhealthy" individuals. This measure was then summed and divided by household size to obtain the "proportion of unhealthy members."

(Table 1 continued)

Variable	Control group (*Treated* = 0)				Experimental group (*Treated* = 1)			
	Mean	Standard deviation	Min.	Max.	Mean	Standard deviation	Min.	Max.
Average educational attainment	3.538	1.830	1	11	3.998	1.983	1	11
Unhealthy family member ratio	0.338	0.456	0	1	0.294	0.348	0	1
Children dependency ratio	0.137	0.168	0	1	0.121	0.155	0	1
Family indebtedness (in debt = 1)	0.289	0.453	0	1	0.233	0.423	0	1
House ownership (household owner = 1)	0.598	0.490	0	1	0.555	0.497	0	1
Financial market participation (yes = 1)	0.039	0.193	0	1	0.063	0.244	0	1
Community type (urban = 1)	0.351	0.477	0	1	0.560	0.496	0	1

Source: Authors' calculations based on the data from the China Labor Dynamics Survey.

IV. Empirical findings

1. Baseline results

The analysis began by evaluating the overall effect of Broadband China pilot city designation on household consumption disparities. Table 2 presents the corresponding regression results, derived from Equation (1). Column (1) presents two-way fixed effects estimates without control variables, with heteroskedasticity-robust standard errors. Columns (2) and (3) sequentially incorporate control variables related to demographic characteristics and household assets and liabilities, respectively, to account for potential influences on household consumption disparities. The results demonstrate that the estimated effect of Broadband China pilot city designation on household consumption deprivation was negative and statistically significant at the 5 percent level, regardless of the set of control variables included. These findings suggest that the expansion of network infrastructure played a significant role in mitigating intra-group consumption inequality and narrowing household-level consumption disparities. Specifically, column (3) reports a coefficient of −0.018 for the core explanatory variable, indicating that Broadband China pilot city designation reduced the Kakwani deprivation index by approximately 0.1 standard deviation. This effect was statistically significant and economically meaningful, providing empirical support for Hypothesis 1.

Table 2. Baseline regression results

Variable	*RCD*		
	(1)	(2)	(3)
Broadband	−0.018** (0.007)	−0.019** (0.007)	−0.018** (0.007)
Hukou of the household head		−0.012 (0.012)	−0.011 (0.012)
Average age		−0.003*** (0.001)	−0.004*** (0.001)
Average educational attainment		−0.015*** (0.003)	−0.014*** (0.003)
Unhealthy family member ratio		−0.009 (0.007)	−0.005 (0.007)
Children dependency ratio		0.089*** (0.028)	0.088*** (0.027)
Family indebtedness			−0.041*** (0.005)
House ownership			−0.011** (0.005)
Financial market participation			−0.041*** (0.011)
Community type	No	Yes	Yes
Household FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	40,280	40,280	40,280

Source: Authors' calculations based on the data from the China Labor Dynamics Survey.

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively, with heteroskedasticity-robust standard errors in parentheses. FE, fixed effects.

However, the consumption deprivation index provides an aggregate measure and does not allow for the identification of specific groups that experienced improvement or reduction in consumption. To address this limitation, the study employed quantile regression to investigate heterogeneous effects across various quantiles of the consumption distribution. The corresponding results are reported in Table A1 in the Appendix. The findings indicate that the policy had a significant positive impact on consumption among households at the 25th percentile of the distribution. These heterogeneous effects suggest that, although the lowest-income group did not experience significant gains, households at the 25th percentile saw a measurable improvement in consumption. Notably, the policy had no significant effect on consumption among wealthier households. As such, the overall decline in consumption deprivation can be attributed largely to improvements among households near the lower end of the distribution. Control variables such as educational attainment, household indebtedness, and homeownership were also found to alleviate consumption deprivation, consistent with prior research findings (Zhang and Yao, 2020).

2. Robustness tests

(1) Parallel trends test

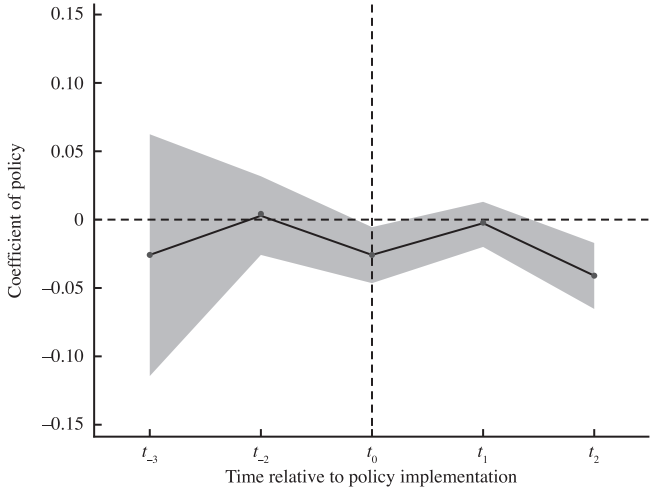
The validity of the DID model relies on the parallel trends assumption, which requires that, prior to the implementation of the Broadband China program, there were no significant differences in consumption disparities between the treatment and control groups. To assess this assumption, an event study approach was adopted based on Equation (1), with the corresponding specification provided in Equation (3). In this framework, $Broadband_{jt}^{k}$ is a dummy variable indicating the *k*th survey period following the implementation of the Broadband China program.[5] β_k represents the estimated effect for each respective period. To examine both the parallel trends and the dynamic impacts of the policy, it is necessary to establish a reference period to avoid multicollinearity. The year immediately preceding the pilot city designation was therefore defined as the baseline period. β_k thus measures changes in relative consumption deprivation between the treatment and control groups, relative to this pre-implementation benchmark.

$$RCD_{ijt} = \beta_0 + \beta_k \sum\nolimits_{k=-3}^{2} Broadband_{jt}^{k} + \gamma \boldsymbol{Control}_{ijt} + \tau_i + \nu_t + \varepsilon_{ijt}. \tag{3}$$

Figure 1 presents the results of the parallel trends test. There were no statistically significant differences in consumption deprivation between the treatment and control groups prior to the implementation of the Broadband China program. This finding confirms the validity of the parallel trends assumption and strengthens the credibility of the DID model estimates. Following the establishment of pilot cities, households in the treatment group experienced a significant decline in relative consumption deprivation in comparison with their counterparts in the control group. To further reinforce the robustness of these results and capture policy effects over a longer time horizon, an additional parallel trends test was conducted using the 2010–2022 China Family Panel Studies dataset. The results from this alternative dataset (Figure A1 in the Appendix) consistently supported the parallel trends assumption, indicating no significant pre-treatment differences between the two groups.

[5]For example, for the 2014 policy, the 2012 questionnaire corresponds to the period immediately preceding the policy implementation, whereas the 2018 questionnaire corresponds to two periods after the policy implementation.

Figure 1. Parallel trends test (China Labor Dynamics Survey)



Source: Drawn by the authors based on the China Labor Dynamics Survey.
Note: The shaded region indicates the 95 percent confidence interval.

(2) The actual impact of becoming a demonstration city

Pilot cities are typically characterized by advanced network infrastructure. However, concerns remain that these cities may slow post-designation infrastructure development, while nondemonstration cities may accelerate their efforts in response. To examine this possibility, a probit model was estimated using a binary indicator for whether a household had Internet access in the previous year. As reported in column (1) of Table 3, designation as a pilot city was positively associated with household Internet use, although the effect was not statistically significant. Columns (2) and (3) present separate estimates for urban and rural subsamples. The results show a significant increase in Internet adoption among rural residents, whereas the impact in urban areas was limited, likely due to already high baseline penetration rates. These findings suggest that the effectiveness of the policy has not declined over time and continues to exceed that of nondemonstration cities. To further validate these results, city-level infrastructure factors, such as mobile subscriptions, 4G base stations, employment in the information sector, and Internet user counts, were incorporated to assess whether the policy led to measurable improvements in the treatment group. The evidence confirms that the demonstration city policy enhanced these infrastructure indicators significantly (Table A2 in the Appendix). These results highlight the critical role of network infrastructure in bridging the digital access gap, enabling vulnerable groups to benefit from the digital dividend, consistent with findings by Leng (2022).

Table 3. The construction of pilot cities and the status of household Internet access

Variable	Internet access (full sample)	Internet access (urban)	Internet access (rural)
	(1)	(2)	(3)
Broadband	0.044	−0.082	0.115**
	(0.038)	(0.079)	(0.048)
Controls	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	36,837	10,838	25,878

Source: Authors' calculations based on the data from the China Labor Dynamics Survey.

Notes: ** represents significance at the 5 percent level. Heteroskedasticity-robust standard errors are in parentheses. Columns (1)–(3) preserve the complete set of controls from column (3) of Table 2. FE, fixed effects.

(3) The omitted variables problem

The causal relationship between the implementation of the Broadband China program and consumption inequality might have been confounded by omitted variables, such as regional economic development, conventional infrastructure, and public expenditures. Oster's (2019) boundary test was employed to address potential endogeneity concerns arising from such omissions. In this approach, R_{max}, the maximum explanatory power of the model, is typically set to 1.3 times the goodness of fit of the baseline model specification, under the assumption that all relevant unobservable variables were observable. The test results yielded an Oster's delta of −1.777; unobserved confounders would have to be 1.777 times more influential than the observed covariates to nullify the estimated DID effect. The setting $\delta = 1$ yielded a bias-corrected DID estimate of −0.034, which, while attenuated relative to the baseline effect in Table 2, remained statistically robust. Notably, the associated identification interval [−0.034, −0.018] excluded zero, reinforcing the statistical credibility of the estimate. Taken together, the results from Oster's test provide additional evidence that the observed relationship was not driven by omitted variable bias and that the main findings remain robust to unobserved confounding.[6]

(4) Excluding contemporaneous policy interference

Although the results suggest that Broadband China pilot city designation mitigated consumption deprivation, potential confounding from concurrent policy interventions in

[6]The boundary test procedure directly generates numerical results without additional regression tables. Following the convention in the literature (e.g., Wu and Su, 2024), we incorporate the outcomes directly into the textual explanation rather than presenting them separately.

treated cities must be considered carefully when attributing causal effects. Prior studies have shown that initiatives such as the establishment of information consumption pilot cities (He and Zhang, 2022) and the promotion of e-commerce development (Jiang et al., 2023) may also have affected household consumption within the same regions. As a result, the baseline estimates may not have fully isolated the effect of the Broadband China program. The analysis addressed this issue by sequentially incorporating controls for overlapping policies into the baseline regression. The estimated effects remained robust and statistically significant, as reported in columns (1)–(3) of Table 4, thereby supporting the validity and reliability of the main findings.

Table 4. Exclusion of potential confounding network infrastructure impact

Variable	*RCD*		
	(1)	(2)	(3)
Broadband	−0.021*** (0.008)	−0.027*** (0.008)	−0.028*** (0.008)
Information consumption policy	0.008 (0.007)		0.002 (0.008)
National e-commerce demonstration policy		0.027*** (0.008)	0.027*** (0.008)
Controls	Yes	Yes	Yes
Household FE	Yes	Yes	Yes
City FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Observations	40,280	40,280	40,280

Source: Authors' calculations based on the data from the China Labor Dynamics Survey.

Notes: *** represents significance at the 1 percent level. Heteroskedasticity-robust standard errors are in parentheses. Columns (1)−(3) include the full set of controls from column (3) of Table 2. FE, fixed effects.

(5) Other robustness tests

To ensure the robustness of our findings, we implemented multiple sensitivity analyses across alternative specifications and subsamples, and reported in detail in Table A3 in the Appendix.

One approach addressed potential endogeneity arising from cities' inherent characteristics and their nonrandom assignment to the treatment group. The standard DID specification was extended by incorporating interaction terms between city-specific characteristics and time trends, following the methodology described by Li et al. (2016). These included interactions between the time trend and city-level variables such as the number of mobile phone subscribers at year end, the number of broadband Internet users, and the number of employees in the information transmission, computer services, and software sectors. The regression results remained robust to these additions.

The second method is to adjust for outcome characteristics. Adjustment for outcome characteristics. Recognizing that the Kakwani index is constrained within the [0, 1] interval, a panel Tobit specification was adopted to model the censored nature of the dependent variable appropriately. The results consistently showed a statistically significant reduction in consumption deprivation associated with the Broadband China policy, regardless of the inclusion of control variables.

A third robustness check addressed potential biases stemming from the administrative hierarchy of cities. The analysis excluded centrally administered municipalities and pilot-designated prefecture-level cities, narrowing the sample to county-level cities to improve comparability and identification credibility.

A fourth analysis examined the issue of negative weighting in staggered DID designs, which can bias estimates when treatment effects are heterogeneous. A two-way fixed effects DID estimator was applied in accordance with the framework proposed by De Chaisemartin and D'Haultfœuille (2020). Among the 212 estimated average treatment effects on the treated, 189 were positively weighted and 23 were negatively weighted. The aggregate weight of the positive estimates was 1.012, and the negative estimates summed to –0.012, indicating that the potential bias from negative weighting was negligible. These findings suggest that treatment effect heterogeneity exerted minimal influence on the estimated coefficients, reinforcing the robustness and credibility of the baseline results.

V. Mechanisms

The baseline findings show that the improvement of Internet infrastructure contributed to the alleviation of individual-level consumption deprivation, effectively attenuating intra-group consumption disparities. However, the underlying mechanisms remain unclear. This section considers the channels through which the effects may operate. It begins by estimating regression Equation (4) to evaluate whether the core explanatory variable significantly influenced the proposed mediating variable (*M*). It then further analyzes the effect of *M* on relative consumption deprivation (*RCD*), thereby shedding light on the underlying transmission channels and the plausibility of the proposed mechanism.

$$M_{ijt} = \beta_0 + \beta_1 Broadband_{jt} + \gamma \boldsymbol{Control}_{ijt} + \tau_i + \nu_t + \varepsilon_{ijt}. \quad (4)$$

In Equation (4), *M* is the mechanism variable, which includes income deprivation and social capital. The rest of the variables are the same as in Equation (1).

1. Income deprivation mitigation effect

According to the permanent income-life cycle hypothesis, consumption decisions are largely driven by individuals' expectations of long-term income. This theoretical framework underscores the importance of income inequality as a fundamental driver of disparities in household consumption patterns (Aguiar and Bils, 2015). Complementing this perspective, information search theory posits that when individuals face high search costs, their ability to make optimal decisions in labor market participation, production, and other economic activities is constrained due to informational frictions and incomplete knowledge (Mortensen and Pissarides, 1999). In this context, improvements in regional Internet infrastructure play a critical role in lowering information friction for marginalized groups, facilitating more equitable access to knowledge and technological resources (Goldfarb and Tucker, 2019). Enabled by robust network infrastructure, the digital economy has catalyzed the emergence of flexible labor markets and entrepreneurial ecosystems, substantially expanding employment and self-employment opportunities for individuals previously constrained by information asymmetries (Leng, 2022; Wei and Wei, 2023). By facilitating poverty alleviation and augmenting income-generating capacity, enhanced Internet access is anticipated to mitigate income deprivation. This reduction in deprivation is likely to reshape household consumption dynamics and foster incremental aggregate demand.

Replacing household consumption expenditure with annual household income in Equation (2) allows for the construction of a comparable income deprivation index, enabling an assessment of deprivation from the perspective of income rather than consumption.[7] As columns (1) and (2) of Table 5 show, the estimated coefficients for the core explanatory variable are significantly negative at the 1 percent level, providing robust evidence that the implementation of the Broadband China program significantly mitigated relative income deprivation among residents. The coefficient in column (3) indicates that income deprivation is significantly positive at the 1 percent level, suggesting that income deprivation aggravated consumption deprivation. We further regress individual-level income deprivation and find similarly negative effects (Table A4 in the Appendix). Taken together, these findings imply that the Broadband China program contributed to the reduction of consumption deprivation primarily through its effect on alleviating household-level income deprivation.

[7]Household consumption expenditure was further replaced with individual annual income to construct an income deprivation indicator, which was subsequently included as an explanatory variable in Equation (2) and incorporated into Equation (4). The regression results remained robust to this alternative specification.

2. Social capital accumulation effect

Broadband Internet functions as a critical enabler of social connectivity, facilitating both the preservation of established relationships and the formation of new social networks. Within the institutional environment of China, social capital endogenously formed through interpersonal networks serves as a key informal mechanism for mitigating risk and stabilizing household consumption (Fafchamps and Gubert, 2006; Liu and Wang, 2017). Historically, interpersonal exchanges and reciprocal support within kinship and social networks were constrained by temporal uncertainty and geographic dispersion. The extensive rollout of digital infrastructure under the Broadband China program has markedly enhanced individuals' access to the Internet, enabling more efficient and accessible online social engagement (Pénard and Poussing, 2010). Bauernschuster et al. (2014) exploited a quasi-natural experiment based on unintended technological decisions by telecommunications providers in 1990s East Germany, and found that broadband Internet access enhanced individuals' social capital. Building on this line of inquiry, Yin et al. (2019) provided evidence that the proliferation of mobile payment technologies expands social networks and significantly increases the likelihood of entrepreneurial engagement. Moreover, a growing body of empirical work underscored the role of social capital in alleviating both income and consumption deprivation among socioeconomically disadvantaged groups (Cull et al., 2022; Yang and Zhang, 2024).

The implementation of the Broadband China program fostered the endogenous accumulation of household-level social capital, which subsequently mitigated relative consumption deprivation within local reference networks. Following Liu and Wang (2017), this study proxied household-level social capital by the log-transformed value of annual expenditure on favors and gift-giving. Columns (5) and (6) of Table 5

Table 5. Mechanism results: Income deprivation and social capital

	Relative income		*RCD*	Social capital		*RCD*
	(1)	(2)	(3)	(4)	(5)	(6)
Broadband	−0.023*** (0.008)	−0.022*** (0.008)		0.327*** (0.123)	0.323*** (0.122)	
Income deprivation			0.262*** (0.010)			
Social capital						−0.008*** (0.001)
Controls	No	Yes	Yes	No	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	31,320	31,320	31,320	40,022	40,022	40,022

Source: Authors' calculations based on the data from the China Labor Dynamics Survey.

Notes: *** represents significance at the 1 percent level. Heteroskedasticity-robust standard errors are in parentheses. Columns (1)–(6) include the full set of controls from Column (3) of Table 2. FE, fixed effects.

show that the initiative had a significant positive effect on household social capital. Increased social capital among socioeconomically disadvantaged groups played a key role in reducing their relative deprivation. These results are consistent with Zhang and Qu (2024), who found that Internet access enabled economically disadvantaged households to increase their income through improved employment opportunities and entrepreneurial activity. By leveraging enhanced social capital, these groups strengthened their economic resilience and became the principal beneficiaries of reduced consumption deprivation.

VI. Further analysis

1. Individual heterogeneity in the sharing of the digital dividend

The preceding analysis examined the influence of Internet infrastructure on relative consumption deprivation, with a particular emphasis on the mechanisms through which this effect materialized. A natural extension of this inquiry is to assess whether the observed effects exhibit heterogeneity across distinct population subgroups. As van Deursen and van Dijk (2019) argued, the digital divide does not vanish with widespread Internet availability; rather, it persists in more nuanced forms, most notably in varying capacity to utilize digital technologies effectively, driven by variations in digital literacy and usage proficiency. Building on the framework advanced by Liu and Wang (2021), the current study systematically investigated heterogeneous treatment effects by stratifying the sample along several key sociospatial dimensions: urban versus rural residence, interregional economic development levels, demographic age cohorts, and intensity of Internet engagement. In this context, regional-level variables serve to capture structural disparities in Internet access, while age and usage intensity are employed to reflect functional disparities in digital literacy and usage capability. Incorporating these moderating variables enriches our understanding of how multiple dimensions of the digital divide shape the relationship between Internet infrastructure and consumption inequality. Table 6 presents the empirical estimates derived from this heterogeneity analysis.

As columns (1) and (2) of Table 6 show, the effects of broadband infrastructure are disproportionately larger in rural areas and in the less developed central and western regions. This pattern suggests that the Broadband China program has served a compensatory role by mitigating consumption deprivation among historically underserved groups with limited digital access and constrained economic resources. Columns (3) and (4) show that the policy's impact was particularly pronounced among younger cohorts and individuals with high levels of Internet usage – groups typically characterized by stronger

Table 6. Heterogeneity results

Variable	*RCD*				
	(1)	(2)	(3)	(4)	(5)
Broadband	−0.038*** (0.010)	−0.051*** (0.004)	−0.011 (0.008)	0.109* (0.058)	0.007 (0.012)
Broadband × Rural area	−0.038*** (0.013)				
Broadband × Central and western region		−0.032* (0.019)			
Broadband × Young group			−0.027* (0.015)		
Broadband × Internet usage intensity				−0.015* (0.008)	
Broadband × Market segregation					−0.204** (0.082)
Controls	Yes	Yes	Yes	Yes	Yes
Household FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	40,280	23,813	40,280	14,437	38,761

Source: Authors' calculations based on the data from the China Labor Dynamics Survey.

Notes: ***, **, and * represent significance at the 1, 5, and 10 percent level. Heteroskedasticity-robust standard errors are in parentheses. The control variables also include the moderator variable. The sample in column (4) consists of Internet users, reflecting the role of the second-level usage divide in the context of the elimination of the first-level access divide. Since the absolute value of the market segmentation index is too small, we multiply the index by 1,000 in order to make the regression coefficients more readable. FE, fixed effects.

digital literacy and greater technological adaptability.[8] Overall, the heterogeneity analysis suggests that while the initiative enhanced access in underdeveloped regions, individuals with greater digital competency ultimately benefited the most. In contrast, individuals with limited digital skills continued to face disproportionately higher levels of consumption deprivation. These findings provide empirical support for Hypothesis 2 and indicate that narrowing the digital access divide alone may be insufficient for reducing consumption inequality. Instead, persistent disparities in digital capability must be addressed to realize inclusive digital outcomes. Importantly, differences in

[8]The CLDS dataset primarily covers the working-age population. Given this study's household-level focus, economic variables such as income and consumption remain representative, as household consumption already accounts for children and elderly members. The main group potentially omitted comprises households in which both the head and the spouse are elderly. To address this limitation, supplementary analysis was incorporated using data from the four waves (2011–2018) of the China Health and Retirement Longitudinal Study, which focused on older populations. The results, reported in Table A5 in the Appendix, confirm the robustness of this study's main findings, indicating that the policy did not exert a significant impact on elderly households (aged 45 and above).

the effective use of digital technologies are shaped not only by the diffusion of ICT infrastructure but also by individual and household endowments, including disparities in physical and human capital. Drawing on data from Taobao villages, Couture et al. (2021) showed that only 15 percent of households engage in e-commerce, and these are typically younger and more affluent. This skewed adoption pattern underscores the urgency of incorporating digital literacy training for socioeconomically disadvantaged groups as a core component of the Digital China strategy.

2. Regional market segmentation

Market segmentation continues to hinder the integration of China's domestic economy and poses a substantive challenge to the realization of a unified national market (Liu and Kong, 2021). Empirical evidence from Wei and Wei (2023) indicated that the poverty-alleviation benefits of network infrastructure expansion were disproportionately larger in areas with pronounced market fragmentation, suggesting that digital connectivity may partially offset institutional and structural inefficiencies.

To capture potential spatial heterogeneity, the analysis was extended to examine whether the impact of network infrastructure development on consumption inequality varied systematically across regions with different levels of market segmentation. A province-level market segmentation index was constructed, following Lu and Chen (2009), by measuring deviations from the Law of One Price across provincial borders relative to the previous year. This index, derived from interprovincial disparities in commodity price indices, reflected the degree of spatial price fragmentation and was interacted with the policy treatment to assess heterogeneous effects.

Assuming there are K categories of goods, the average absolute price index change $\left|\Delta P_{mnt}^{k}\right|$ between province m and province n for product k was first computed, denoted as $\overline{\Delta P^{k}}$. Next, the relative price change component for each product k was defined as $p_{mnt}^{k}=\left|\Delta P_{mnt}^{k}\right|-\overline{\Delta P^{k}}$. Finally, the variance in p_{mnt}^{k} was calculated across the K product categories, denoted as $Var(p_{mnt})$. To quantify market segmentation in province m, an index was constructed based on the average interprovincial variance in relative price deviations across 21 commodity categories between province m and all other provinces. Let N represent the total number of other provinces, this segmentation index can be expressed formally as:

$$semg_{m}=\frac{\left[\sum_{m\neq n}Var\left(p_{mnt}\right)\right]}{N}. \tag{5}$$

As shown in column (5) of Table 6, the estimated coefficient is significantly negative, which indicates that the mitigating effect of the Broadband China program on consumption deprivation was amplified in provinces exhibiting greater degrees of market segmentation, where structural frictions in resource allocation tended to be more pronounced. Taken together, these results underscore the critical role of digital infrastructure in mitigating market fragmentation, facilitating more efficient interregional transactions, and fostering the institutional and logistical foundations necessary for the development of an integrated national market.

3. Subjective welfare inequalities

The preceding analysis considered objective welfare inequality, measured by household consumption deprivation. However, the policy may also affect individuals' subjective evaluations of inequality. Material forms of relative deprivation were expected to influence residents' perceived positional disadvantage within their social reference group. To examine this subjective dimension, the baseline outcome variable – objective relative deprivation in consumption – was replaced with perceptual indicators: perceived relative deprivation and subjective poverty. The CLDS survey included a question eliciting subjective perceptions of relative deprivation: "Compared with your peers, do you think your current standard of living is better or worse than that of the following people?" The reference group comprised residents in the respondent's municipal district or county. Responses ranged from "much higher" to "much lower," coded from 1 to 5, with higher values indicating greater perceived relative deprivation. Subjective poverty captures an individual's perceived economic hardship, reflecting a holistic appraisal of their material living standards and psychosocial well-being (Li and Cai, 2024). Respondents who rated their socioeconomic position as 1 or 2 on a 10-point scale were classified as the "subjective poverty" group, and a corresponding dummy variable was constructed.

Table 7. Subjective impacts results

Variable	Relative deprivation perception	Subjective poverty
	(1)	(2)
Broadband	−0.114***	−0.043***
	(0.044)	(0.011)
Controls	Yes	Yes
Household FE	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	28,481	39,116

Source: Authors' calculations based on the data from the China Labor Dynamics Survey.

Notes: *** represents significance at the 1 percent level. Heteroskedasticity-robust standard errors are reported in parentheses. Control variables include: individual age, education level, political profile (if this individual is a member of the Communist Party of China), social insurance, *hukou* status, homeownership, and financial market participation. Since only three questionnaires asked about "relative deprivation" in 2014, 2016, and 2018, the sample from the first model cities of 2014 is excluded from column (1). FE, fixed effects.

Columns (1) and (2) of Table 7 provide compelling evidence that cyberinfrastructure development significantly attenuated both objective measures of relative deprivation and subjective perceptions of poverty, with estimated effects highly significant at the 1 percent level. Taken together, these findings highlight the dual-channel welfare-enhancing role of digital infrastructure, simultaneously improving individuals' material living standards and their perceived socioeconomic status.

4. Policy comparison

The preceding analysis highlighted the central role of the Broadband China program in reducing foundational disparities in digital access and advancing inclusive development. A critical question, however, concerns whether consumption inequality may worsen if digital infrastructure expansion prioritizes access speed over the inclusion of vulnerable populations. To explore this issue, the analysis contrasted the current context with the 2000 Internet Speed-up Project – an infrastructure initiative that established the National Internet Exchange Center in Beijing and increased the bandwidth of China's core interconnection backbone from below 10 Mbps to 100 Mbps, representing a major shift in national network capacity. Microdata from the China Household Income Project for the period 1995–2007 were used to empirically test this hypothesis. The empirical framework follows the baseline specification introduced by Chen and Liu (2022):

$$RCD_{ijt} = \beta_0 + \beta_1 Infrastructure_{j,1999} \times Post2001_t + \gamma \boldsymbol{Control}_{ijt} + \sigma_j + \nu_t + \varepsilon_{ijt}. \quad (6)$$

The variable $Infrastructure_{j,1999}$ captures baseline Internet infrastructure conditions, proxied by the landline telephone penetration rate in city j in 1999. The indicator $Post2001$ denotes the post-shock period and takes the value of 1 for years from 2001 onward, and 0 otherwise. The results are reported in Table 8.

The Internet Speed-up Project significantly boosted consumption levels in urban areas, whereas no discernible effect was observed in rural regions, highlighting the unequal distribution of digital infrastructure benefits during the early phase of broadband expansion. The policy appears to have narrowed intra–urban consumption disparities but it simultaneously exacerbated inequality in rural areas. In contrast to the latter, more inclusive, Broadband China program, bandwidth-focused infrastructure upgrades that fail to ensure equitable access may deepen regional consumption divides, disproportionately impacting marginalized populations. These findings underscore the importance of addressing the foundational layer of the digital divide before shifting emphasis toward optimizing network performance.

Table 8. Internet Speed-up Project (2000)

Variable	Urban		Rural	
	Consumption	*RCD*	Consumption	*RCD*
	(1)	(2)	(3)	(4)
Infrastructure × *Post*2001	12.685*** (2.382)	−0.004*** (0.001)	−2.500 (1.765)	0.002* (0.001)
Controls	No	Yes	No	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	15,073	15,073	15,204	15,204

Source: Authors' calculations based on the data from the China Household Income Project.

Notes: *** and * represent significance at the 1 and 10 percent levels, respectively. Heteroskedasticity-robust standard errors are reported in parentheses. The Kakwani index was calculated at the district and county level where urban and rural individuals were located (the smallest unit in the dataset). Control variables included financial market participation, home ownership, family size (number of family members), and household income. To make it easier to interpret the coefficients, landline telephone penetration rates are divided by 10 in Columns (2) and (4). FE, fixed effects.

Nevertheless, in 2002, digital device penetration across Chinese households remained limited, thereby constraining the potential impact of early broadband initiatives. However, the effects of broadband infrastructure extended beyond computer-owning households, potentially benefiting those with mobile phone access as well. For instance, Wan et al. (2021) provided evidence that, in rural contexts, the beneficial effects of broadband expansion were predominantly channeled through mobile Internet use rather than traditional computer-based access. Given the relatively widespread ownership of mobile phones, the rollout of broadband infrastructure likely exerted a measurable influence on household consumption behavior even in the absence of computers. Drawing on data from the 2002 Urban Household Survey, this study quantified digital inclusion in urban China by estimating household-level ownership rates of mobile phones and personal computers, thereby providing an empirical context for the technological baseline. The data reveal marked disparities between cities, with average urban household ownership rates of 13 percent for mobile phones and just 2.8 percent for personal computers.

VII. Conclusion

This study examined how variations in broadband infrastructure rollout can affect the distribution of household consumption. Using a staggered DID design and household-level panel data, it found that increased access to broadband reduced relative consumption deprivation, particularly among groups with lower initial connectivity.

The effects operated through both income gains and the accumulation of social capital, which is consistent with models where infrastructure lowers frictions in labor markets and informal insurance networks.

These results contribute to a broader understanding of how public infrastructure can shape economic outcomes at the household level. Despite the rising focus on digital services, our results indicate that how and when digital infrastructure is expanded can also exert meaningful impacts on distributional outcomes. The contrast between access-oriented and speed-oriented policies highlights the importance of considering heterogeneity in both exposure and adoption when evaluating large-scale technology investments. While the integration of micro-level outcomes with quasi-experimental variation in infrastructure provision is now widely adopted in empirical research, this study demonstrates its continued value in unpacking the distributional implications of digital infrastructure rollout. In particular, it shows how such an approach can reveal heterogeneous effects beyond average outcomes – highlighting differences across households in inequality, mobility, and welfare. Future research could build on this by examining how differential access interacts with digital skills, institutional settings, or labor market dynamics to shape these returns.

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Appendix

Table A1. Quantile regression results for network infrastructure and household consumption expenditure

Variable	Consumption (in log form)				
	(1) (q = 10th)	(2) (q = 25th)	(3) (q = 50th)	(4) (q = 75th)	(5) (q = 90th)
Broadband	0.059 (0.076)	0.098** (0.049)	0.039 (0.037)	0.043 (0.037)	−0.008 (0.069)
Controls	Yes	Yes	Yes	Yes	Yes
Individual FE	Yes	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Observations	40,280	40,280	40,280	40,280	40,280

Source: Authors' calculations based on the data from the China Labor Dynamics Survey.

Notes: ** represents significance at the 5 percent level, with heteroskedasticity-robust standard errors in parentheses. Control variables include average age, average level of education, average health status, number of family members, number of people with medical insurance, and number of children. FE, fixed effects.

Table A2. The improvement effect of the policy on the network infrastructure of pilot cities

Variable	Mobile phone subscribers	Internet broadband access subscribers	4G base station	Employees in the information industry
	(1)	(2)	(3)	(4)
Broadband	29.521* (17.400)	17.123 (16.090)	1.685*** (0.279)	1.458*** (0.561)
Controls	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	1,723	1,714	1,149	1,729

Sources: Authors' calculations based on the data from the *China City Statistical Yearbook* and OpenCelliD.

Notes: *** and * represent significance at the 1 and 10 percent levels, respectively. Estimated coefficients are followed by robust standard errors. Control variables at the city level include economic development level, fiscal expenditure level, and industrial structure. Economic development is measured by the logarithm of per capita GDP in the city where residents reside. Industrial structure is measured by the proportion of the added value of the secondary industry in GDP. Fiscal expenditure is measured as a proportion of general public budget expenditure in GDP. Column (3) uses the sample period from 2014 to 2018, and the rest are consistent with the baseline regression. FE, fixed effects.

Table A3. Other robust checks

Variable	*RCD*			
	(1)	(2)	(3)	(4)
Broadband	−0.018** (0.008)	−0.020*** (0.004)	−0.009** (0.004)	−0.016** (0.008)
Mobile phone subscribers × Trend	Yes	No	No	No
Internet broadband access subscribers × Trend	Yes	No	No	No
Employees in the information industry × Trend	Yes	No	No	No
Controls	Yes	No	Yes	Yes
Individual FE	Yes	No	No	Yes
Year FE	Yes	Yes	Yes	Yes
City FE	Yes	Yes	Yes	Yes
Observations	35,292	40,280	40,280	38,254

Source: Authors' calculations based on the data from the China Labor Dynamics Survey.

Notes: *** and ** represent significance at the 1 and 5 percent levels, respectively. Column (1) controls for cross-multiplication of city intrinsic characteristics with the time trend term, and columns (2) and (3) are both estimated using Tobit estimation with panel random effects, except for column (2), which does not incorporate the household control variable. Column (4) is estimated for a sample of prefecture-level cities excluding municipalities and those whose policy pilot is a county-level city. FE, fixed effects.

Table A4. Mechanism results: Income deprivation at individual level

Variable	Relative income deprivation	
	(1)	(2)
Broadband	−0.030*** (0.008)	−0.029*** (0.008)
Controls	No	Yes
Individual FE	Yes	Yes
Year FE	Yes	Yes
City FE	Yes	Yes
Observations	37,837	36,837

Source: Authors' calculations based on the data from the China Labor Dynamics Survey.

Notes: *** represents significance at the 1 percent level. Heteroskedasticity-robust standard errors are reported in parentheses. Control variables in columns (1) and (2) include individual age, education level, political profile, social insurance, *hukou* nature, homeownership, and financial market participation. FE, fixed effects.

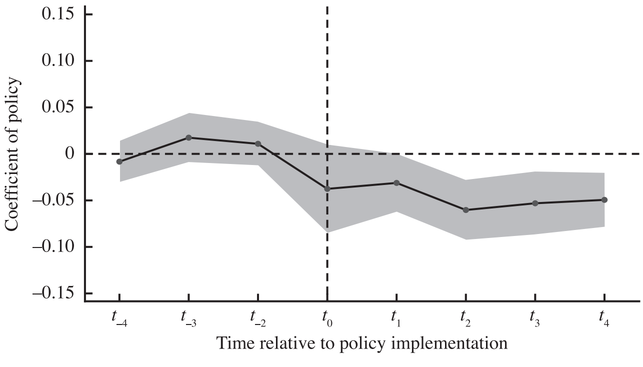
Table A5. Regression results with respect to the sample of the elderly

Variable	*RCD*	
	(1)	(2)
Broadband	0.008	0.015
	(0.014)	(0.014)
Controls	No	Yes
Household FE	Yes	Yes
City FE	Yes	Yes
Year FE	Yes	Yes
Observations	11,468	11,468

Source: Authors' calculations based on the data from the China Health and Retirement Longitudinal Study.

Notes: Heteroskedasticity-robust standard errors are reported in parentheses. Control variables include average age, average level of education, average health status, number of family members, number of people with medical insurance, and number of children. FE, fixed effects.

Figure A1. Parallel trends test (China Family Panel Studies)



Source: Drawn by the authors based on the China Family Panel Studies.

Note: The shaded region indicates the 95 percent confidence interval.

(Edited by Shuyu Chang)